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ORIGINAL PAPER

A first generation dynamic ingress, redistribution and transport model of soil track-in: DIRT

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Abstract This work introduces a spatially resolved quantitative model, based on conservation of mass and first order transfer kinetics, for following the transport and redistribution of outdoor soil to, and within, the indoor environment by track-in on footwear. Implementations of the DIRT model examined the influence of room size, rug area and location, shoe size, and mass transfer coefficients for smooth and carpeted floor surfaces using the ratio of mass loading on carpeted to smooth floor surfaces as a performance metric. Results showed that in the limit for large numbers of random steps the dual aspects of deposition to and track-off from the carpets govern this ratio. Using recently obtained experimental measurements, historic transport and distribution parameters, cleaning efficiencies for the different floor surfaces, and indoor dust deposition rates to provide model boundary conditions, DIRT predicts realistic floor surface loadings. The spatio-temporal variability in model predictions agrees with field observations and suggests that floor surface dust loadings are constantly in flux; steady state distributions are hardly, if ever, achieved.

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Introduction

Urban soils and dusts represent significant reservoirs for a variety of non-volatile and toxic environmental contaminant species such as heavy metals, PAH's and pesticides (Lambert and Lane 2004; Lemley et al. 2002; Lewis et al. 1994). Human exposure to these substances is increasingly associated with indoor activity through contact with dusts internal to the built environment. Both the health effects and the environmental quality determinants of indoor dust have received substantial attention in recent years (Paustenbach et al. 1997; Kildeso et al. 1999; Tong and Lam 2000; Pesonen-Leinonen et al. 2004; Turner and Simmonds 2006; and others). However, substantial knowledge gaps exist for the transport, partitioning and removal processes by which soil contaminants present indoor exposure risks. Since people in the United States spend most of their time indoors (Klepeis et al. 2001), two-thirds of it in residential settings, human health risk assessments focusing on such toxic materials need to consider the material flux between the outdoor soil reservoirs and the indoor sites of exposure as well as the associated conveyance mechanisms.

The mechanical transport of soil and dust on footwear is a major vector for the ingress of outdoor contaminants to the indoor environment (Lioy et al. 2002). The work of Cannell et al. (1987), and the more recent study by Hunt et al. (2006) for both wet and dry soils, have quantified the deposition of particle mass to floor surfaces. The latter study reinforces the observations of Laxen et al. (1988) and Al-Radady et al. (1994) that outdoor soil loading on interior floors is greater during wet weather periods than dry ones. Farfel et al. (2001) and von Lindern et al. (2003) measured soil ingress fluxes directly, using short-term deployment of building entrance floor mats. When scaled for the size of the collection media, observations showed 50–300 mg of external soil brought into the houses each day; a value of 200 mg per day was characteristic of urban environments (Baltimore, MD, USA). Radioactive tracer measurements in Barrow-in-Furness (UK) by Allott et al. (1994) after the Chernobyl accident indicated a steady state flux of about 190 mg per day.

Except for the work of Allott et al. (1994) above, quantitative models incorporating floor dust loading have been restricted to the phenomenon of resuspension. Early work by Raunemaa et al. (1989), based on indoor/outdoor ratios and bulk elemental composition of aerosol samples, resulted in a fate and transport model for particles in indoor air, including a resuspension component. Thatcher and Layton (1995) connected size-specific particle resuspension and deposition in a residence with activity patterns of the occupants. While their results relate resuspension to floor dust loading, they did not include a soil/dust ingress component in the model structure. Schneider et al. (1999) were able to model indoor surface dust loadings, but did not provide interior spatial resolution or associate variability of the predictions with the flux of track-in material. The present work provides an interface between the model development noted above and the influx and deposition of outdoor particulate mass resulting from the track-in process. Its basis is the conservation of total mass between footwear and floor surface compartments as the mass transfer process occurs during random walk ingress events taking place in a spatially resolved indoor environment.

Model description

Computational basis

The experimental results of Hunt et al. (2006), recalculated for this work, indicate the transfer of soil particles from footwear to clean floor tile surfaces follows a first order kinetic process (Fig. 1). Each step deposits the same fraction of shoe track-in mass onto the smooth surface, although the transfer coefficients depend upon the nature of the shoe sole texture. The conceptual model for transfer envisions the intimate contact of two surfaces having different proportions of adhesion sites occupied by soil particles. Mass is transferred from the more densely populated surface to the less densely populated one in proportion to the difference in mass per unit area of contact. Thus, the track-on to clean floors by dirty footwear and the track-off from dirty floor tiles by clean footwear are both governed by the same first order transfer coefficient.

For carpeted floor surfaces, the transfer phenomenon is slightly more complex than for smooth surfaces. Cannell et al. (1987) used a fluorescent tracer and video imaging to follow the movement of material from smooth-sole footwear to carpet surfaces; they did not report results for treaded-sole shoe/carpet tracking experiments. After stepping in the tracer, a subject walked with alternate steps around a circle of 12 carpet tiles; the tracer mass distribution on the tiles was monitored periodically as traverses around the loop continued. Data recalculated from their results show that initial transfer of material from footwear to clean carpets appears to follow first order kinetics (Fig. 1). However, with continued traversals as in their Group 4 results (60 cycles, 720 steps total), an additional carpet track-off parameter is required to explain the transport observations. The conceptual model for transfer replaces the infinitely thin, two-dimensional, contact surface

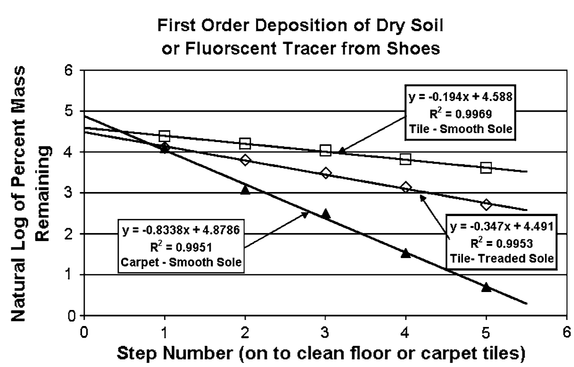

Fig. 1 First order particle mass deposition from footwear track-in experiments by Hunt et al. (2006) and Cannell et al. (1987)

(described above) with a three-dimensional contact volume wherein the net transfer of particle mass from footwear to carpet is governed by two types of binding. An irreversible binding, apparently first order with respect to mass on the shoe sole, drives particle transfer from the footwear to the carpet. A reversible binding component, apparently first order with respect to carpet mass loading, results in carpet track-off. The net transfer of mass from shoe to carpet is a linear combination of these two dependencies. Figure 2 illustrates how this two-component binding model fits the experimental results of Cannell et al. (1987). Trial and error combinations of the reversible and irreversible binding coefficients were employed until the best visual fit was obtained between the model computations and the empirical results. The equations for the fit lines to the data are illustrated, and regression coefficients were calculated for those fits only for the purpose of comparing them.

Algorithm implementation

FORTRAN 95 is used to perform the spatial mass distribution computations that simulate the track-in process for a residential space with dimensions of up to 25 × 50 feet (c. 762 × 1,524 cm). An array of up to 2,500 × 5,000 elements of floor plan space each covering 0.01 sq feet (3 × 3 cm) is established for the conservation of mass accounting. Random x, y locations for the endpoint of step movement are generated, scaled to the spatial elements of the floor plan for a given run. A trigonometric sub-routine,

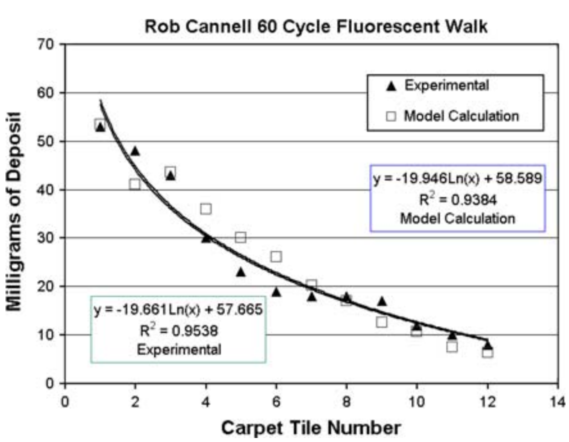

Fig. 2 Comparison of observed and predicted particle mass transfer from footwear to carpet surface following extended traversal cycles; calculated from Cannell et al. (1987)

using a specific stride length, computes the floor plan address where the upper left hand corner of each shoe print is to be placed for each random traversal series of alternating left and right steps. Then the next random endpoint of movement is determined, and the series of step locations to reach it are computed, the process continuing for a user specified number of movement locations.

In the equations below, the soil mass in each of the floor plan elements is represented by the variable $fpm_{x,y}$. Footwear surfaces are defined with an integer number of identically sized spatial elements arranged in a square array. The soil mass in each of the footwear elements is represented by the variable $sml_{i,j}$ or $smr_{i,j}$ for left and right shoes. Particle mass transfer to or from each of these elements is computed at each floor plan location covered by the footwear elements associated with a particular step. For each shoe sole element placed during the random walk, either the smooth floor or the carpeted surface kinetics governs mass transfer computation. Separate computations are undertaken for right and left shoes in case some asymmetry in the random walk is desired.

If a shoe sole element falls on a smooth tile surface, the following program statements are executed:

$$\mathrm{trans}_{i,j} = \mathrm{sml}_{i,j} - \mathrm{fpm}_{x,y} \tag{1a}$$

$$\mathrm{fpm}_{x,y} = \mathrm{fpm}_{x,y} + \mathrm{trans}_{i,j} * \mathrm{tile} \tag{1b}$$

$$\mathrm{sml}_{i,j} = \mathrm{sml}_{i,j} - \mathrm{trans}_{i,j} * \mathrm{tile} \tag{1c}$$

where $trans_{i,j}$ is the difference in mass between the shoe loading $sml_{i,j}$ (for left shoe array element i,j) and the floor plan mass loading $fpm_{x,y}$ (for array element x,y), computed by Eq. 1a; the fraction of the mass difference specified by the transfer coefficient, *tile*, is added to the floor by Eq. 1b; and subtracted from the shoe sole mass by Eq. 1c. The algebraic sign for the variable $trans_{i,j}$ is preserved; a clean shoe surface picks up soil from a dirty floor element and vice versa. In similar fashion, if a shoe sole element falls on a carpeted surface, transfer computations are governed by

$$\mathrm{fpm}_{x,y} = \mathrm{fpm}_{x,y} + \mathrm{sml}_{i,j} * \mathrm{rug} \tag{2a}$$

$$\mathrm{sml}_{i,j} = \mathrm{sml}_{i,j} - \mathrm{sml}_{i,j} * \mathrm{rug} + \mathrm{toff} * \mathrm{fpm}_{x,y} \tag{2b}$$

$$\mathrm{fpm}_{x,y} = \mathrm{fpm}_{x,y} - \mathrm{toff} * \mathrm{fpm}_{x,y} \tag{2c}$$

where the subscripts have the same meaning as above; *rug* is a first order transfer coefficient for carpeted surface in Eq. 2a; a fraction of the carpet dust mass is added back with the track-off coefficient, *toff*, in Eq. 2b; and a similar amount is removed from the floor surface spatial element in Eq. 2c.

User inputs and model outputs

The primary use of the (present first generation) model is as a predictive tool for the spatio-temporal distribution of track-in soil/dust mass on floor surfaces. Consequently, a wide variety of user specifications are employed in its operation. Chief among these is floor plan for the simulations. The user can specify the location and extent of smooth floor and carpeted floor surface coverings, the location of interior walls and openings, and the placement of furniture where no foot traffic is to be allowed. These floor plan attributes are specified in an integer array (at 3-cm resolution), where element values of 0 represent smooth floor, 1 indicates carpet surface, and 2 designates furniture. Created by a spreadsheet program or text editor, they are read in as an external text file at the beginning of each batch run. Size of footwear is indicated by the number of (3×3 cm) spatial elements comprising one side of a square array of such units; thus, foot print areas are in the range of 36–441 sq cm. Stride length is indicated by an integer number of these same elements. Simulations begin with an entry from the outside environment where the footwear carries a specified particulate mass followed by a designated number of random moves before the next entry cycle. The number of daily entry cycles, each carrying a proportional fraction of designated soil ingress flux, can be adjusted as desired.

Computational parameters are fixed at run time for the mass transfer coefficients governing smooth floor, the carpeted surfaces and the track-off from the latter. Additionally, the user may elect to simulate floor-cleaning activities utilizing dust removal efficiencies established individually for each model run. Finally, the user may specify an indoor dust deposition flux to be deposited on all floor surfaces as a supplement to the track-in loading; the indoor dust fall is allowed to accumulate under any furniture designated in the floor plan.

Model output takes the form of a spatial distribution of floor dust loading at the conclusion of the simulation; it is available at both the 0.1-foot (c. 3-cm) and 1.0-foot (c. 30-cm) resolutions. If a vacuum-cleaning regimen has been specified, the spatial floor dust distribution is recorded at the conclusion of each cleaning event. This allows for following the dust build up on carpeted surfaces due to poor removal efficiency.

Model performance metric

Simulations by the model were evaluated with various combinations of input parameters; the ratio of mass loading on carpet surface to that on smooth floor (R_{rt}) was used as the comparison metric. It is widely accepted that carpets are a significant reservoir for particulate contaminant species indoors (Bero et al. 1997; Roberts et al. 1999; Fortune et al. 2000; Yiin et al. 2000), and several studies provide comparisons of floor dust loading and carpet dust loading. With about 100 houses (500 samples) in the CLEARS study, data from Lioy et al. (1998) show a geometric mean ratio of rug to floor loading of 14 (GSD $\sim$ 3). With a subset of these results, values reported by Yiin et al. (2000) indicate the ratio, R_{rt} to range of 11.1 during the hot season to 24–25 during cool and cold periods; again, the GSD values for the measures were approximately 3.0. For the soil and dust study in Syracuse, NY, (Johnson et al. 2005, 2008) 98 vacuum cleaner dust samples were collected from 61 different households during the summers of 2003 and 2004 by the method of Watt et al. (1983). The GM value of R_{rt} for those 61 residences was 11.3 (3.6–36, at GSD of 0.5).

To examine the influence of model parameter combinations on the ratio, R_{rt}, a simple floor plan was defined. It consisted of a single room 6×16 feet (c. 183×488 cm) with an entry in the upper left hand corner; in the lower right hand corner, a rug 3×8 foot (c. 91×244 cm) was located (25% of total floor area). Model runs of 250,000 steps incorporated: various shoe sizes; stride lengths; rug area and location; and various values of the transfer coefficients K_t for smooth floor, K_r for carpeted surfaces and T_{off} for carpet track-off. (Simulations did not include vacuum cleaning cycles.) Results of this quasi-sensitivity analysis showed three significant aspects of the track-in process:

- No stable steady state distribution of mass on both types of floor surfaces can exist simultaneously unless a carpet track-off term is included in the soil/dust ingress and redistribution process. In the limit, with a track-off coefficient (T_{off}) of zero, all of the transported mass will reside on the surface for which the higher transfer coefficient applies.

- For a non-zero value of carpet track-off, the steady state value of the loading ratio, R_{rt}, is not affected by: room size, carpet size and location, shoe size, stride length, or K_t, the smooth floor transfer coefficient. These variables are *dynamic parameters*; they affect the rate of attainment of the steady state condition, but they do not define it. Figure 3 (below) illustrates this, plotting the average Rug loading to Tile loading ratio as a function of the number of random steps for the simulation and the size of shoe modeled. In this example, $K_r = 0.654$ and $T_{off} = 0.020$.
- The steady state mass loading ratio R_{rt} is controlled only by the *fundamental parameters* K_r and T_{off}. In the limit, the loading ratio is defined by:

$$R_{rt} = K_r / T_{off} \qquad (3)$$

Model predictions

To examine whether the model predicts mass loading values comparable to field observations, an enlarged floor plan and more realistic activity pattern were created. The simulation was carried out in 2 rooms; an 8 × 9 foot (c. 244 × 274 cm) kitchen (smooth floor) and an 8 × 12 foot (c. 244 × 366 cm) living room with a smooth floor but containing a 5 × 6 foot (c. 152 × 183 cm) carpet in the main walkway. A 3 × 6 foot (c. 91 × 183 cm) table was placed between the end of the carpet and the wall of the room; no random steps occurred under the table. The activity pattern was based on four ingress events per day; (1) enter and walk randomly in kitchen; (2) enter and walk randomly in a 3-foot (c. 91 cm) traffic path extending from kitchen through living room; (3) enter, transit to living room, then walk randomly; (4) repeat transit sequence 2. Each of the transit events contained one half the number of steps of the kitchen and living room random walks. Indoor dust deposition to all floor surfaces, including under the table, was allowed to occur; floor mass loading was uniformly incremented at the end of each ingress cycle. A vacuum-cleaning regimen for all floor surfaces, except that under the table, was introduced at a 2-week frequency. The smooth floor cleaning efficiency was specified at 95% while that for the carpeted surface was set at 50% (Bero et al. 1997). Table 1 summarizes the operational parameters for this example of model predictions.

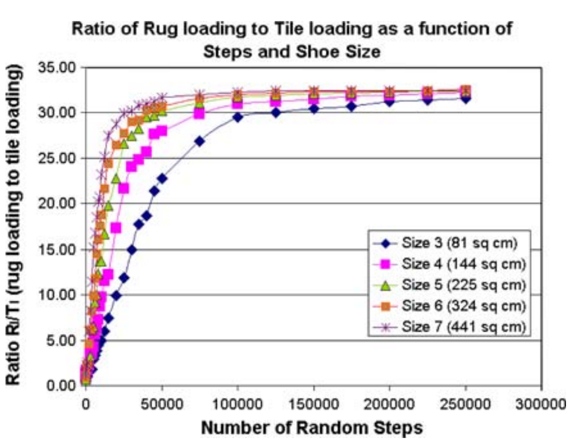

Fig. 3 The dynamic variable effect; how attainment of the steady state rug to tile loading ratio is approached as a function of shoe size and the number of random steps

Figure 4 displays the floor dust loading patterns for this simulation after 2, 14 and 180 days. The maps (from ArcMap 9.1) have been generated from the full spatial resolution of 100 pixels per sq foot (c. 929 sq cm), and clearly indicate the model traffic patterns. Spatial heterogeneity with the small shoe size is apparent as is the role of the carpet in sequestering the dust, particularly in the transit corridor. Note that the lookup table for floor dust loading is exponential. In the 6-month map, lower right, the influence of the background indoor dust deposition can be observed where it has accumulated to over 60 mg per sq foot (c. 929 sq cm) based on the summer season deposition rate of Edwards et al. (1998). In its current configuration, the model does not account for particle resuspension.

Table 2 is a digital representation of the loading distribution summarized for each square foot of floor surface, as is produced in normal program output. Model parameters are those listed in Table 1, except as noted. The number of moves was increased to 200 to represent random walk distribution by two individuals. The results are shown for 2 months of uniform track-in events. Floor dust loading in the kitchen averaged about 16 mg ft^2 (c. 929 sq cm)—about 4 times the smooth floor loading observed in the living room. Carpet dust loadings in the high traffic pattern area averaged about 200 mg ft^2 but dropped off to about 1/3 of that outside the high traffic area. All these

Table 1 Simulation parameters utilized for spatio-temporal floor dust loading predictions

Soil ingress rate	200 mg per day
Indoor dust deposition flux	300 µg ft^{-2} day^{-1} (c. 0.3 µg cm^{-2} day^{-1})
Shoe size	81 cm^2 (size 3)
Stride	12 (36 cm; ∼5 steps per move)
Ingress events	4 per day
Random move endpoints per cycle	100 for kitchen & living room walk (50 for transit walk events)
Smooth floor transfer coefficient, K_t	0.345
Carpet transfer coefficient, K_r	0.654
Carpet track-off coefficient, T_{off}	0.020
Vacuum cleaning frequency	14 days
Smooth floor vacuuming efficiency	95%
Carpet vacuuming efficiency	50%

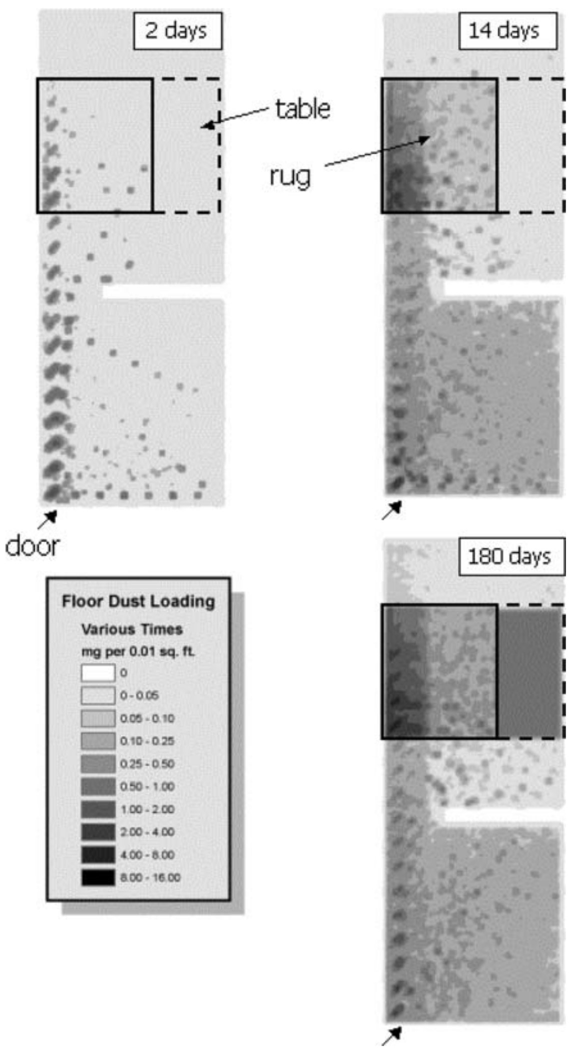

Fig. 4 Predicted floor dust loading after various time periods (see Table 1 for details of simulation parameters)

Table 2 Program output for a 2-month simulation, where results are reported as mg dust per square foot (c. 929 sq cm) of floor

0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	5.9	5.3	4.0	3.7	3.6	3.8	3.6	3.8	0.0
0.0	6.0	4.8	3.5	3.3	3.4	3.3	3.3	3.6	0.0
0.0	7.0	5.2	3.7	3.5	3.6	3.2	3.3	3.8	0.0
0.0	189.2	136.4	69.8	64.8	62.0	19.2	19.2	19.4	0.0
0.0	208.4	150.6	75.0	67.2	64.1	21.0	21.0	21.0	0.0
0.0	216.3	152.1	78.0	71.5	64.9	21.0	21.0	21.0	0.0
0.0	247.6	179.4	76.9	75.8	67.8	21.0	21.0	21.0	0.0
0.0	272.5	198.3	82.0	75.6	70.0	21.0	21.0	21.0	0.0
0.0	276.9	200.2	77.9	72.2	67.9	21.0	21.0	21.0	0.0
0.0	10.7	7.8	3.9	3.9	3.8	3.6	3.4	3.7	0.0
0.0	12.0	9.5	5.2	4.3	3.9	3.5	3.8	3.6	0.0
0.0	12.3	12.1	5.4	4.6	4.1	4.1	4.0	4.3	0.0
0.0	13.2	10.6	3.7	0.0	0.0	0.0	0.0	0.0	0.0
0.0	14.6	12.2	13.9	13.6	13.8	14.1	14.2	12.8	0.0
0.0	16.4	14.8	16.1	16.3	16.1	16.4	15.8	14.1	0.0
0.0	14.8	13.8	16.2	16.0	17.4	16.4	15.9	14.7	0.0
0.0	15.8	13.9	16.0	16.8	16.5	16.5	16.0	14.4	0.0
0.0	18.0	14.4	16.4	16.6	16.7	16.3	16.3	14.7	0.0
0.0	19.2	14.7	17.3	16.2	16.1	16.4	16.3	14.7	0.0
0.0	17.0	14.8	16.9	16.4	16.6	16.5	17.0	14.7	0.0
0.0	17.8	15.7	18.1	18.5	16.5	16.7	16.6	14.7	0.0
0.0	24.9	16.0	17.5	17.8	17.3	16.5	17.3	14.9	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Run parameters are those indicated in Table I except: shoe size = 5 (225 sq cm), stride length = 15 (45 cm), and random move endpoints per cycle = 200. The two-room floor plan, as in Fig. 4, covers an interior space of 8 feet (c. 244 cm) (columns 2–9) by 22 feet (c. 670 cm) (rows 2–23). Walls are indicated by array entries of 0.0; entry door is at columns 2–3 in row 24. Carpeting covers columns 2–6 in rows 5–10; a table is present at columns 7–9 in rows 5–10 loading values are consistent with field observations from Syracuse, NY, as is the average carpet loading (123 mg ft^2) to smooth floor loading (12 mg ft^2) ratio of slightly over 10. Substantial spatial heterogeneity was observed for the floor dust loading, a direct result of the floor plan specifications as well as the selection of activity pattern.

Discussion and conclusions

Several factors lead to the creation of the DIRT model and continue to drive its development.

1. The lack of appropriate indoor sampling data may limit pollutant exposure models and human health risk assessments. Predictions from the model can help to refine sampling regimes and protocols.
2. Obtaining adequate environmental monitoring data for the indoor environment is complex and substantially more expensive than mapping exercises undertaken to evaluate outdoor soil contamination. Such sampling for building empirical databases is destructive; model simulations can, in some cases, be cost effective for understanding the dynamics of track-in exposure pathways.
3. The time scale of how acute outdoor events might influence the indoor environment currently has little predictive basis. Model results can address that limitation.

The model description and its implementation described here should be considered as prototypical for proof of concept. It does not currently allow for environmental variability in such parameters as activity pattern, stride length, shoe sole type, multiple different carpet transfer characteristics, etc. It does, however, allow user specification of fixed values for a large number of run parameters covering shoe size, stride length, duration of random walking events, track-in mass fluxes, cleaning regimen schedules and background dust deposition through keyboard entry at the beginning of each batch run. Similarly, cleaning efficiencies, floor plan configurations and the required transfer coefficients are easily altered by simple editing of the external floor plan text file. However, program code must be edited and recompiled for implementation of different activity patterns or for implementation of "spill events" where the rate and extent of the track-off dynamic is to be investigated. The model would be significantly improved and perhaps enjoy some limited investigative application if it incorporated a module for easy specification of indoor activity patterns.

The conservation of mass employed in this model configuration provides realistic spatio-temporal floor dust distributions when combined with known soil ingress rates and indoor dust deposition fluxes. Given the large number of parameters included in the computational approach, several key conclusions are suggested:

1. The model framework is a useful quantitative tool for examination of the indoor transport dynamics of floor dust and for evaluation of the efficacy of various floor-cleaning regimes.
2. Some indoor dust resuspension and aerosol transport models (e.g., Thatcher and Layton 1995; Schneider et al. 1999) have been implemented across particle size classes and may serve as the basis for dust contaminant inhalation risks. If the DIRT algorithm was to be made similarly particle size range specific, it could easily interface with, and improve the accuracy of, such exposure assessment models by connecting them more closely to the outdoor pollutant reservoirs
3. The DIRT model is suitable for conversion to a probabilistic form. Such development will require a larger set of environmental observations, more detailed investigation of the transfer kinetics, and, perhaps most importantly, a refinement of floor dust sampling protocols so that results can be more easily utilized between investigators.

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